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Particle filter approach to lifetime prediction for microelectronic devices and systems with multiple failure mechanisms

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ABSTRACT

Lifetime prediction for microelectronic devices and systems is complicated by many factors including the validity of linear acceleration, choice of extrapolation model, presence of multiple failure mechanisms with common driving forces, correlation between failure mechanisms, time-variant loading (voltage pulses) etc… With real-time prognostics and health management coming up as a useful alternative to conventional post-failure reliability data analysis, significant progress has been made in estimating the individual lifetime of microelectronic devices/systems during operation (real-time). In this study, we present a case study of decoding the contributions of the bias temperature instability (BTI) and hot carrier injection (HCI) mechanisms to the overall time-dependent threshold voltage (V_{TH}) shift observed in real-time during a conventional HCI stress test applied to a single NMOS device. Assuming no prior knowledge of the time exponents for V_{TH} degradation for both the BTI and HCI mechanisms, our methodology enables us to deconvolute the overall V_{TH} data signal, predict the remaining useful life (RUL) for the device (given a threshold failure criterion) and extract the distribution of the power-law exponents for the pure-HCI and pure-BTI mechanisms. We used the particle filter based sequential Monte Carlo (SMC) technique here for the prognostic study and the advantage of our approach is its generic use for non-linear systems and non-Gaussian noise trends. The impact of prognostics based data-driven algorithms in dynamic lifecycle estimation of microelectronic devices is evident in this work and such an approach can be handy in high-power space electronics applications when the reliability (health/robustness) of a single device (integrated in the satellite) needs to be studied (under normal operating conditions) and there is no large sample size population of similar devices available for a conventional accelerated stress test exercise off-field. To our knowledge, this is the first study applying the particle filter technique for a multiple failure mechanism scenario. The accuracy of our RUL estimates was compared with real data extracted from past experimental studies.

1. Introduction

The need for real-time prognostics and health management (PHM) of microelectronic devices and systems has become imperative in various applications including avionics, space, defense, transportation and telecommunication systems. Tracking the performance of these mission critical systems and estimating their remaining useful life (RUL) well in advance can help pre-determine maintenance schedules, ensure optimum system availability and help minimize downtime and maintenance costs (spare part requirements) quite significantly. Power electronic devices and batteries are particularly vulnerable to failures in such systems. The complexity arises when such systems degrade simultaneously under the influence of more than one mechanism, where the multiple mechanisms could be dependent and correlated to one another in an unknown fashion. To address this scenario, in this study, we present a methodology for estimation of the RUL distribution and extraction of parameter values corresponding to two embedded failure mechanisms, validated using a case study analyzing threshold voltage degradation (V_{TH}) data in real-time on a stressed NMOS transistor device which was investigated for hot carrier reliability. The hot carrier stress schema usually causes the transistor V_{TH} to increase due to both positive bias temperature instability (PBTI, here on referred to simply as BTI) as well as hot carrier injection (HCI) [1,2]. When we only have information on the total V_{TH} trend, it is essential to be able to extract the individual contributions of BTI and HCI with certain level of confidence. The particle filter (PF) technique [3–5], which is a sequential Monte Carlo (SMC) procedure is a popular data-driven method for PHM analysis of any system with an underlying phenomenological/physical degradation model. We shall use this technique and benefit from its generic framework that makes it suitable for modeling non-linear systems and non-Gaussian noise trends (process/measurement perturbations) as well.

The flow of the paper is organized as follows. Section 2 emphasizes the need for prognostics in microelectronic devices/systems and

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explains the Bayesian updating and inference based PF methodology. Section 3 provides the details of the test carried out by Masada et al. [6] and the V_{TH} data extracted from their work for validating our PHM approach in this study for the bimodal failure scenario. Section 4 then presents the results of our PF algorithm, the extracted RUL distributions and predicted trends of parameter values for the commonly assumed power-law formulation of V_{TH} degradation [7,8]. Finally, Section 5 concludes with a summary of the work and its other possible applications to different microelectronic device technologies.

2. Need for prognostics and particle filter methodology

The need for PHM as a tool for lifecycle management of microelectronic devices/systems is evident from the illustration in Fig. 1. While traditional reliability studies only provide an overall distribution of the lifetime of the sample set of systems stressed purposely to failure at accelerated test conditions, the PHM approach is more customized and real-time as it tracks the current state and evolution trend of degradation and uses that information to make an inference on the RUL of that particular system being studied. Therefore, the lifetime distribution estimate is fully customized to the health of each unit being sensed in contrast to the broader population of failure time distributions that standard reliability analysis would provide us with. The need for PHM is more apparent in mission critical technologies such as space electronics as well as systems with complex (often not well understood) failure phenomena such as batteries where the need for real-time health estimation is necessary to maximize time-averaged availability of the system in the field. With no stress acceleration involved during PHM studies, the risk of introducing new failures is drastically reduced, which is not the case for conventional reliability tests with high acceleration factors.

The working principle of the PF algorithm is shown in Fig. 2. It is essentially a sequential Monte Carlo approach whereby the posterior distribution of the degradation model parameters is updated after every new sensor data (additional measurement point) arrives, using the likelihood function for weighting the "particles". For every new cycle, the previous posterior distribution is considered as the new prior distribution; while for the first cycle, the values for the prior distribution parameters are assumed based on user's knowledge of the system. The Monte Carlo nature of the algorithm here comes from the sampling of the "particles" belonging to a distribution and propagation of these particles in a directed manner using the relative likelihood value as the importance function. The key highlight in the PF algorithm is the "resampling" of particles based on the likelihood value so as to confine the parameters to a certain region in the space where their optimal value to fit the observed degradation trend is most likely to exist. The prior distribution for the parameters are generally assumed to be Gaussian. Typically, around 5000–10,000 particles are used for the simulation in order to get robust RUL distribution estimates. At any point of time, for the current state value of the parameters, the future evolution of the system can be predicted, taking into consideration the noise terms in the degradation process model and in the measurements.

3. Threshold voltage degradation measurements

The schematic of the NMOS device and the spatial electric field patterns due to pure-PBTI and pure-HCI contributions is illustrated in Figs. 3(a, b). Data corresponding to the overall increase in the V_{TH} value (denoted here on as $\Delta V_{TH\text{-}TOT}$) was collected from an NMOS metal gated device with HfSiON as the dielectric, with EOT ~1.5 nm and area of 0.55 μm^2. The experiment was conducted by the group of Masada et al. at Toshiba Corporation a few years ago [6]. The data is plotted in Fig. 3(c) and using a novel procedure involving the relation between ΔV_{TH} and J_g (gate tunnel current density), the individual contributions of $\Delta V_{TH\text{-}BTI}$ and $\Delta V_{TH\text{-}HCI}$ were extracted and included in the same plot. For the PHM exercise here, we shall assume that the only data available to us in real-time is $\Delta V_{TH\text{-}TOT}$ and knowing that there are two underlying degradation (failure) components, we try to decode them using the PF approach and estimate the RUL for different sample size of data collected. The trend of $\Delta V_{TH\text{-}TOT}$ degradation can be represented in the power law format as Eq. (1), where A and n are the proportionality constant and power law time exponent respectively. The individual $\Delta V_{TH\text{-}BTI}$ and $\Delta V_{TH\text{-}HCI}$ components can also be considered to have the same form as Eq. (1).

$$\Delta V_{TH(N)} = A \cdot t^n \tag{1}$$

This equation may now be reformulated for future state prediction by expressing the ΔV_{TH} values at successive time steps K and $(K+1)$ using Eq. (2). It is to be noted that the data measurements in Ref. [6] are taken in a regular log time scale and the interval period for successive measurements on the log scale is referred to here as β ~0.3. In

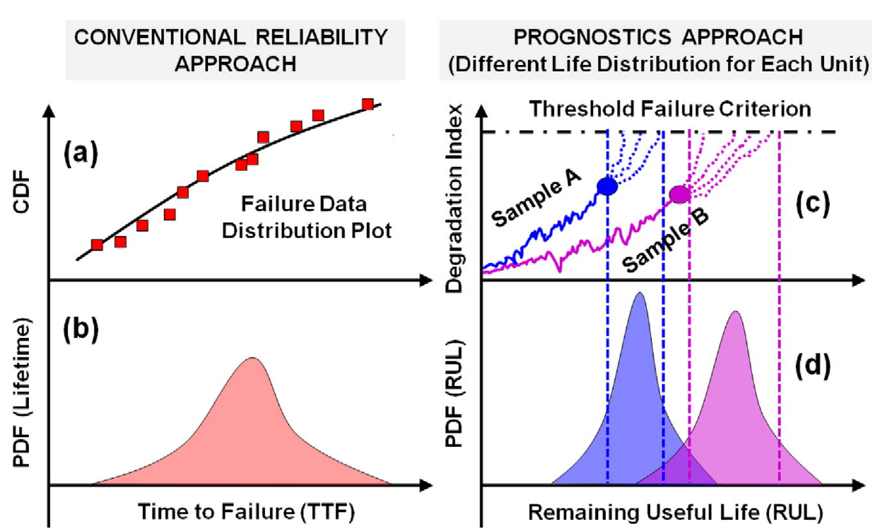

Fig. 1. Comparison of the lifetime estimation approach for conventional reliability analysis and prognostics based analysis. While the conventional approach with failure history data provides a lifetime distribution that is widely spread out, the prognostics approach with individual system condition monitoring provides a more accurate and confined estimate of the remaining life of the system in use. As a result, the prognostics approach is more effective (though more challenging and sophisticated to implement) in optimizing the maintenance and operational resources for any system in general.

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